This a try to perform an analysis on the themes identified in best 100 papers from this github repo (<a href="https://github.com/terryum/awesome-deep-learning-papers">https://github.com/terryum/awesome-deep-learning-papers</a>). This repo suggested a list of top 100 deep learning papers published from 2012 to 2016 according to citation criteria. I based on this source because it would provide more insight than some collections of random papers. Then, a script is used to parse pdfs to plain texts. We concatenate all plain texts to papers.txt which is of size 4 MB. This means there is about **4000000 characters** in the data. The gensim library is used as it is tailored for topic modelling. The findings are visualized by pyLDAvis library and stored as Ida.html. The model used is Latent Dirichlet allocation since it is an unsupervised topic model meaning I do not need to label my data. My repo can be found in <a href="https://github.com/tim1234ltp/understanding-awesome-deep-learning-papers">https://github.com/tim1234ltp/understanding-awesome-deep-learning-papers</a>.

I try to categorize the data to 3 topics/PCs (principal components):

Their visualizations are put in the appendix.

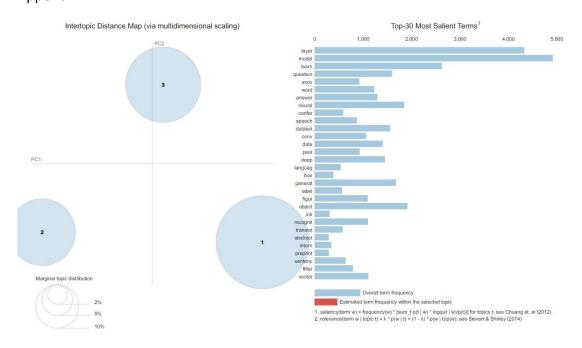
Topic 1 contains [layer, network, feature, train, perform]. showing that this topic is in fact neural network structuring.

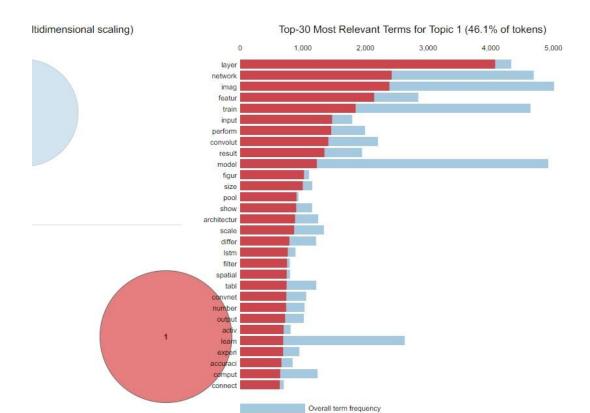
Topic 2 contains [learn, image, arxiv, dataset], showing that this is a topic of data in machine learning.

Topic 3 contains [model, conv, speech, sequence, predict], showing that this is a topic of various machine learning model among different scenarios.

To sum up, these top 100 papers are mainly dominated by neural network with different variations. And some of them spent an effort in discussing datasets they used.

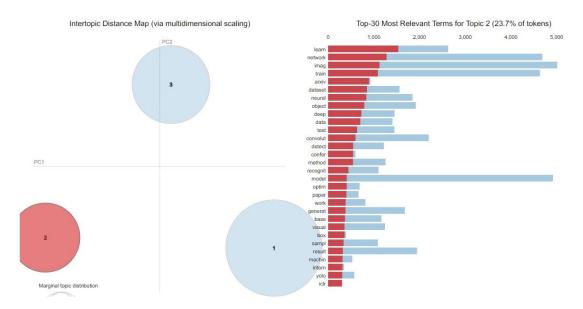
## Appendix:

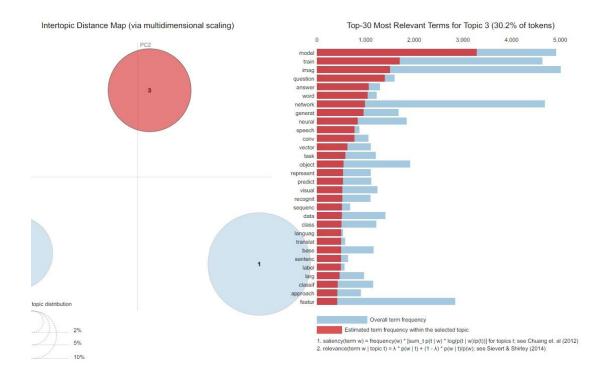




1. saliency(term w) = frequency(w) \* [sum\_t p(t | w) \* log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012) 2. relevance(term w | topic t) =  $\lambda$  \* p(w | t) + (1 -  $\lambda$ ) \* p(w | t)/p(w); see Sievert & Shirley (2014)

Estimated term frequency within the selected topic





## Papers crawled:

Distilling the knowledge in a neural network (2015), G. Hinton et al.

Deep neural networks are easily fooled: High confidence predictions for unrecognizable images (2015), A. Nguyen et al.

How transferable are features in deep neural networks? (2014), J. Yosinski et al.

CNN features off-the-Shelf: An astounding baseline for recognition (2014), A. Razavian et al.

Learning and transferring mid-Level image representations using convolutional neural networks (2014), M. Oquab et al.

Visualizing and understanding convolutional networks (2014), M. Zeiler and R. Fergus Decaf: A deep convolutional activation feature for generic visual recognition (2014), J. Donahue et al.

Training very deep networks (2015), R. Srivastava et al.

Batch normalization: Accelerating deep network training by reducing internal covariate shift (2015), S. Loffe and C. Szegedy

Delving deep into rectifiers: Surpassing human-level performance on imagenet classification (2015), K. He et al.

Dropout: A simple way to prevent neural networks from overfitting (2014), N. Srivastava et al.

Adam: A method for stochastic optimization (2014), D. Kingma and J. Ba Improving neural networks by preventing co-adaptation of feature detectors (2012),

G. Hinton et al.

Random search for hyper-parameter optimization (2012) J. Bergstra and Y. Bengio Pixel recurrent neural networks (2016), A. Oord et al.

Improved techniques for training GANs (2016), T. Salimans et al.

Unsupervised representation learning with deep convolutional generative adversarial networks (2015), A. Radford et al.

DRAW: A recurrent neural network for image generation (2015), K. Gregor et al.

Generative adversarial nets (2014), I. Goodfellow et al.

Auto-encoding variational Bayes (2013), D. Kingma and M. Welling

Building high-level features using large scale unsupervised learning (2013), Q. Le et al.

Rethinking the inception architecture for computer vision (2016), C. Szegedy et al. Inception-v4, inception-resnet and the impact of residual connections on learning (2016), C. Szegedy et al.

Identity Mappings in Deep Residual Networks (2016), K. He et al.

Deep residual learning for image recognition (2016), K. He et al.

Spatial transformer network (2015), M. Jaderberg et al.,

Going deeper with convolutions (2015), C. Szegedy et al.

Very deep convolutional networks for large-scale image recognition (2014), K.

Simonyan and A. Zisserman

Return of the devil in the details: delving deep into convolutional nets (2014), K. Chatfield et al.

OverFeat: Integrated recognition, localization and detection using convolutional networks (2013), P. Sermanet et al.

Maxout networks (2013), I. Goodfellow et al.

Network in network (2013), M. Lin et al.

ImageNet classification with deep convolutional neural networks (2012), A.

Krizhevsky et al.

You only look once: Unified, real-time object detection (2016), J. Redmon et al.

Fully convolutional networks for semantic segmentation (2015), J. Long et al.

Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks (2015), S. Ren et al.

Fast R-CNN (2015), R. Girshick

Rich feature hierarchies for accurate object detection and semantic segmentation (2014), R. Girshick et al.

Spatial pyramid pooling in deep convolutional networks for visual recognition (2014), K. He et al.

Semantic image segmentation with deep convolutional nets and fully connected

CRFs, L. Chen et al.

Learning hierarchical features for scene labeling (2013), C. Farabet et al.

Image / Video / Etc

Image Super-Resolution Using Deep Convolutional Networks (2016), C. Dong et al.

A neural algorithm of artistic style (2015), L. Gatys et al.

Deep visual-semantic alignments for generating image descriptions (2015), A.

Karpathy and L. Fei-Fei

Show, attend and tell: Neural image caption generation with visual attention (2015), K. Xu et al.

Show and tell: A neural image caption generator (2015), O. Vinyals et al.

Long-term recurrent convolutional networks for visual recognition and description (2015), J. Donahue et al.

VQA: Visual question answering (2015), S. Antol et al.

DeepFace: Closing the gap to human-level performance in face verification (2014), Y.

Taigman et al. :

Large-scale video classification with convolutional neural networks (2014), A.

Karpathy et al.

Two-stream convolutional networks for action recognition in videos (2014), K.

Simonyan et al.

3D convolutional neural networks for human action recognition (2013), S. Ji et al.

Neural Architectures for Named Entity Recognition (2016), G. Lample et al.

Exploring the limits of language modeling (2016), R. Jozefowicz et al.

Teaching machines to read and comprehend (2015), K. Hermann et al.

Effective approaches to attention-based neural machine translation (2015), M. Luong et al.

Conditional random fields as recurrent neural networks (2015), S. Zheng and S.

Jayasumana.

Memory networks (2014), J. Weston et al.

Neural turing machines (2014), A. Graves et al.

Neural machine translation by jointly learning to align and translate (2014), D.

Bahdanau et al.

Sequence to sequence learning with neural networks (2014), I. Sutskever et al.

Learning phrase representations using RNN encoder-decoder for statistical machine translation (2014), K. Cho et al.

A convolutional neural network for modeling sentences (2014), N. Kalchbrenner et al.

Convolutional neural networks for sentence classification (2014), Y. Kim

Glove: Global vectors for word representation (2014), J. Pennington et al.

Distributed representations of sentences and documents (2014), Q. Le and T. Mikolov

Distributed representations of words and phrases and their compositionality (2013), T. Mikolov et al.

Efficient estimation of word representations in vector space (2013), T. Mikolov et al. Recursive deep models for semantic compositionality over a sentiment treebank (2013), R. Socher et al.

Generating sequences with recurrent neural networks (2013), A. Graves.

End-to-end attention-based large vocabulary speech recognition (2016), D. Bahdanau et al.

Deep speech 2: End-to-end speech recognition in English and Mandarin (2015), D. Amodei et al.

Speech recognition with deep recurrent neural networks (2013), A. Graves

Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups (2012), G. Hinton et al.

Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition (2012) G. Dahl et al.

Acoustic modeling using deep belief networks (2012), A. Mohamed et al.

Reinforcement Learning / Robotics

End-to-end training of deep visuomotor policies (2016), S. Levine et al.

Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection (2016), S. Levine et al.

Asynchronous methods for deep reinforcement learning (2016), V. Mnih et al.

Deep Reinforcement Learning with Double Q-Learning (2016), H. Hasselt et al.

Mastering the game of Go with deep neural networks and tree search (2016), D.

Silver et al.

Continuous control with deep reinforcement learning (2015), T. Lillicrap et al.

Deep learning for detecting robotic grasps (2015), I. Lenz et al.

Playing atari with deep reinforcement learning (2013), V. Mnih et al. )

Layer Normalization (2016), J. Ba et al.

Learning to learn by gradient descent by gradient descent (2016), M. Andrychowicz et al.

Domain-adversarial training of neural networks (2016), Y. Ganin et al.

WaveNet: A Generative Model for Raw Audio (2016), A. Oord et al. [web]

Colorful image colorization (2016), R. Zhang et al.

Generative visual manipulation on the natural image manifold (2016), J. Zhu et al.

Texture networks: Feed-forward synthesis of textures and stylized images (2016), D Ulyanov et al.

SSD: Single shot multibox detector (2016), W. Liu et al.

SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 1MB model size

(2016), F. Iandola et al.

Eie: Efficient inference engine on compressed deep neural network (2016), S. Han et al.

Binarized neural networks: Training deep neural networks with weights and activations constrained to+ 1 or-1 (2016), M. Courbariaux et al.

Dynamic memory networks for visual and textual question answering (2016), C. Xiong et al.

Stacked attention networks for image question answering (2016), Z. Yang et al. Hybrid computing using a neural network with dynamic external memory (2016), A. Graves et al.

Google's neural machine translation system: Bridging the gap between human and machine translation (2016), Y. Wu et al.